

Long-term increases in station-derived drought near Apalachicola National Forest, Florida

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Revised preprint draft, 15 October 2026

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Revision draft of the April 2022 EarthArXiv preprint [10.31223/X5H350](https://doi.org/10.31223/X5H350). This manuscript has not been peer reviewed.

Abstract

Long local weather records can reveal changes in drought exposure, but a drought index calculated at one station must be distinguished from soil-water measurements across a forest. We updated daily temperature and precipitation observations at Tallahassee airport and recomputed the Keetch-Byram Drought Index (KBDI) with explicit quality control, rainfall interception, and missing-data rules. Across 69 complete eligible annual records spanning 1945-2024, mean moisture deficit increased by 2.63 mm per decade (95% interval: 0.58-4.67), and the annual number of days with KBDI above 650 increased by 2.59 days per decade (0.67-4.51). May showed the clearest monthly drying signal after adjustment for 12 monthly comparisons: 4.64 mm per decade (1.68-7.61; adjusted $p = 0.031$). April's trend remained uncertain. May slopes stayed positive across 27 tested KBDI settings, although uncertainty in high-deficit-day trends depended on the record's starting year. A historical 2009-2018 PRISM comparison showed airport-forest daily anomaly correspondence, with an area-weighted squared correlation of 0.72. As an application, April 30 moisture deficit reduced point-estimate hindcast error for May-July natural-fire counts, but the paired skill interval included no improvement. The strongest evidence therefore concerns increasing station-derived drought exposure and its seasonal structure. It does not establish a forest-wide soil-moisture trend, an anthropogenic attribution, or a validated operational wildfire forecast.

Keywords: Keetch-Byram Drought Index; station record; moisture deficit; seasonal drought; wildfire; Florida.

1. Introduction

Long weather records provide a way to detect changes in local drought exposure that shorter observational networks cannot resolve. Their interpretation requires care: a weather-derived drought index describes a particular response to meteorological conditions, whereas soil moisture, ecological stress, and fire activity depend on additional processes. Recent work has sharpened both the need to assess

change and the need to distinguish these quantities. Hoylman, Bocinsky, and Jencso (2022) show that historical reference periods can misrepresent contemporary drought severity when climate distributions shift. Estimating a long-term trend and classifying present drought against a stationary baseline are therefore different tasks.

The Keetch-Byram Drought Index (KBDI) provides a daily measure of accumulated weather-related moisture deficiency from maximum temperature and precipitation (Keetch and Byram 1968). Its long history in fire applications makes it useful for examining how drying conditions vary across years and seasons. However, the index’s nominal water-deficit units do not make it a measurement of water storage in a specified soil profile. In a national comparison of drought indicators with observed soil moisture, Hoylman et al. (2024) found that correspondence depends on depth and timescale, with several soil-moisture models outperforming the meteorological indices they evaluated. Their study did not directly validate KBDI. It motivates comparing our index with local observations rather than assuming equivalence with measured soil moisture.

Apalachicola National Forest (ANF), in the Florida Panhandle, offers a useful setting for such an assessment. The nearby Tallahassee airport record permits consistent drought-index calculations over eight decades. The regional fire context is also changing: Donovan et al. (2023) report spatially heterogeneous changes in large wildfires across the eastern United States. That regional evidence concerns a different spatial scale and fire response from natural-fire counts in ANF. Western US attribution studies likewise motivate investigation without supplying a local causal explanation (Abatzoglou and Williams 2016).

We ask how annual mean KBDI-derived deficit and high-deficit-day exposure have changed in the station record, and how the changes differ among calendar months. The main contribution is a reproducible assessment of long-term station-derived drought change, with explicit missing-data rules and sensitivity to index settings, record period, serial dependence, and ENSO. A historical PRISM comparison assesses temporal correspondence across the forest footprint. A supplemental comparison with in-situ Wakulla soil moisture examines recent local correspondence and its limitations.

Seasonal wildfire prediction is an application of this drought record. We test whether April 30 deficit improves retrospective forecasts of May-July natural fire counts over a climatological baseline, training each hindcast on preceding seasons. This separates detection of station-derived drought change from the predictive value of a pre-season indicator. It also avoids assuming that a trend in drought must produce an equivalent trend in fires: fuels, ignitions, suppression, and prescribed burning can alter that relationship. Recent southeastern US research treats prescribed burning and wildfire as interacting responses to climate and management (Hashida, Lewis, and Cummins 2025).

This manuscript revises the earlier ANF preprint (Law and Elsner 2022), extending the weather and fire snapshots, correcting the rainfall implementation, and reorganizing the analysis around long-term drought change. The wildfire season and April 30 predictor are retained from that work; the updated hindcasts use preceding-year training and explicitly quantify paired skill uncertainty.

2. Study setting and data

2.1. Airport observations and the forest footprint

We use the Tallahassee airport record, GHCN-Daily station USW00093805, from NOAA’s National Centers for Environmental Information. GHCN-Daily provides quality-controlled historical daily observations suitable for examining local weather variability (Menne et al. 2012; NOAA National Centers for Environmental Information, [n.d.b](#)). The station metadata locate the airport at approximately 30.39354 degrees N, 84.35136 degrees W (NOAA National Centers for Environmental Information, [n.d.a](#)). ANF lies nearby in the Florida Panhandle. The fixed Forest Service administrative polygon used in the original study encompasses approximately 2,567 square kilometers. We retain this footprint rather than allowing administrative-boundary revisions to alter the comparison through time (Figure 1A). It defines the fire-selection area; it is not a measurement of forest cover or a claim that all enclosed land has identical fuels or management.

The updated station snapshot contains observations through 12 October 2026. We begin the calculation on 1 January 1944 and exclude partial calendar years from climate-trend analyses. Complete eligible annual KBDI records span 1945-2024, with gaps; some complete monthly records extend into 2025. The candidate endpoint of 2025 must therefore be distinguished from the actual last year represented in each estimate. Weather observations were not homogenized for station moves, instrumentation, or observation-time changes.

We use daily precipitation and maximum temperature for KBDI and retain minimum temperature for climatic context. Native GHCN units are converted from tenths of millimeters and tenths of degrees Celsius. Values marked missing or having nonblank quality flags are rejected, and the daily calendar is completed explicitly. Trace rainfall uses its reported numerical value. Required-input gaps are not replaced by zero rainfall or undocumented manual fills.

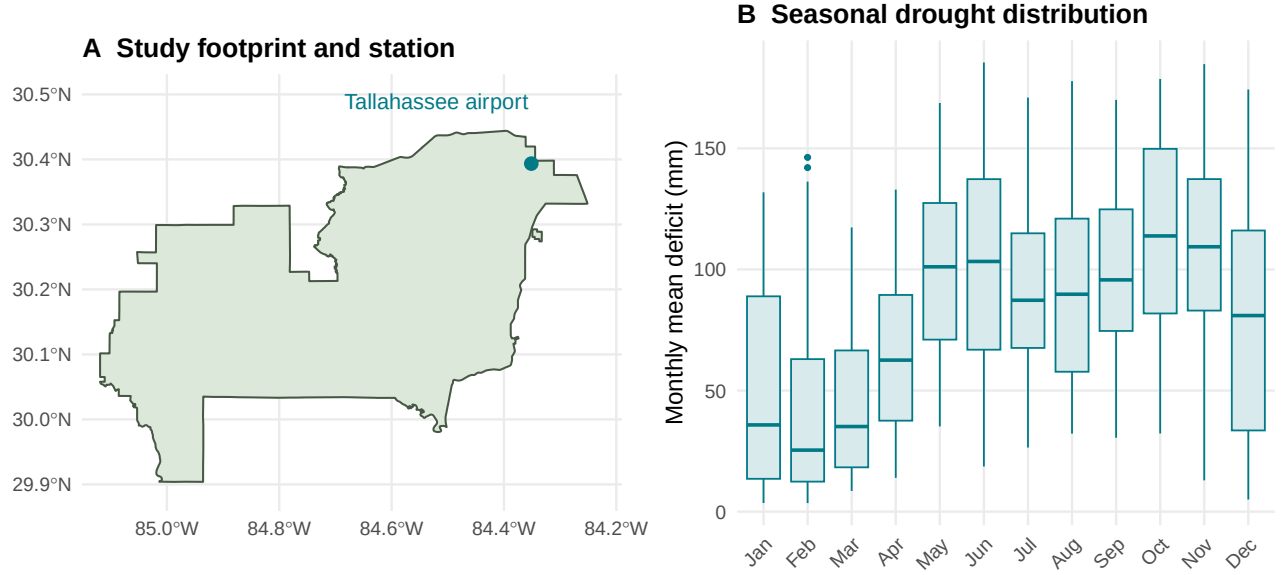


Figure 1. Study setting and seasonal drought distribution. (A) Fixed ANF administrative footprint and the airport weather station (solid dot). (B) Distribution of complete eligible monthly mean KBDI-derived deficits, using available months from 1945-2025. Boxes show the interquartile range, center lines the median, and whiskers extend to 1.5 times the interquartile range; remaining observations are plotted individually.

2.2. Historical gridded comparison

We recompute KBDI from the existing daily PRISM precipitation and maximum temperature archive for 2009-2018 at approximately 4-km resolution (PRISM Climate Group, Oregon State University, [n.d.](#)). The comparison includes 170 cells intersecting ANF, with weights proportional to each cell’s area of overlap with the footprint. Dates and input variables are paired explicitly. Grid calculations use the same KBDI assumptions and spin-up rule as the station calculation. This is a historical correspondence check; the PRISM observations have not been extended beyond 2018.

PRISM incorporates station observations and is not independent of the station network. Its time-series products can also contain inhomogeneities associated with changing observations (PRISM Climate Group, Oregon State University, [n.d.](#)). Neither high temporal correlation over this short period nor the availability of a long airport record establishes spatially homogeneous drought change throughout the forest.

2.3. Independent soil-moisture observations

For an exploratory supplemental comparison, we use the USDA NRCS Wakulla #1 Soil Climate Analysis Network (SCAN) station (2009:FL:SCAN) at 30.30585 degrees N, 84.42477 degrees W (USDA Natural Resources Conservation Service, [n.d.](#)). This location intersects our fixed ANF polygon and is 12.03 km from the airport. Observations begin in December 1996 at depths of 5.08, 10.16, 20.32, and 50.8 cm, and in April 1997 at 101.6 cm. The downloaded record extends to 12 October 2026, with substantial gaps. These are in-situ sensor observations independent of the airport weather inputs, but they describe one soil profile. NRCS documents conversion using a loam equation; undocumented sensor changes

and calibration uncertainty limit interpretation of absolute values and long-term shifts (USDA Natural Resources Conservation Service, [n.d.](#)). The complete comparison rules and diagnostics are given in the supplement.

2.4. Wildfire observations for the application

The seventh edition of the Fire Program Analysis Fire-Occurrence Database (FPA FOD) supplies ignition locations, discovery dates, reported causes, and final sizes for 1992-2024 (Short [2026](#)). We select unique ignition points intersecting the fixed ANF polygon, including boundary points. This yields 1,294 recorded fires, of which 483 are classified as natural. Of the natural fires, 385 (79.7%) were discovered during May-July. We retain this three-month season from the original study rather than searching the updated observations for an optimal prediction window.

Unknown causes remain in the all-fire series. Natural, human, and all-fire responses are kept separate throughout fitting and evaluation. Every archive year is represented in the seasonal counts, including zero-fire seasons. Reported final sizes describe entire fires igniting inside the footprint; they do not measure the area burned within the boundary. Changes in reporting, classification, or management remain possible influences on the fire record.

3. Methods

3.1. Daily drought index and complete-period summaries

KBDI represents cumulative weather-related moisture deficiency (Keetch and Byram [1968](#)). Let Q_t denote the index in hundredths of an inch, T_t daily maximum temperature in degrees Fahrenheit, and R fixed mean annual rainfall in inches. For effective daily rainfall P_t^* in inches, we first reduce the preceding deficit:

$$Q_t^- = \max(0, Q_{t-1} - 100P_t^*).$$

We then calculate the daily drying increment and bound the resulting index:

$$Q_t = \min \left[800, Q_t^- + \max \left\{ 0, \frac{(800 - Q_t^-)(0.968 \exp(0.0486T_t) - 8.3)}{1000[1 + 10.88 \exp(-0.0441R)]} \right\} \right].$$

The metric moisture deficit is $D_t = 0.254Q_t$ millimeters, ranging from 0 to 203.2 mm. These are index-equivalent deficits, not measurements of water stored in a specified soil profile. Effective rainfall removes 0.2 inches of interception once per consecutive wet spell, rather than independently from every rainy day. We correct the original implementation's treatment of consecutive small rainfalls crossing this threshold and subtract effective rain before evaluating the drying increment.

The primary calculation uses $R = 60$ inches and initial $Q = 400$. Here R is a fixed climatological assumption, not the accumulated rainfall in an individual year. Following any missing required input, we restart at 400 and withhold estimates until at least 365 consecutive complete days have accrued. A monthly mean is eligible only if every day in that calendar month has an eligible index. Annual

summaries similarly require every day of the year; annual mean deficit weights months by their day counts. We do not scale partially observed periods to represent complete ones.

We examine two primary annual summaries: mean deficit and the number of days with KBDI greater than 650 (165.1 mm). The latter is an index-specific high-deficit threshold, not a validated local ecological-impact threshold. Monthly means describe seasonal structure (Figure 1B). Complete-period requirements yield 69 annual KBDI records and between 72 and 74 monthly records per calendar month in the updated trend analysis.

3.2. Trend estimates and uncertainty

We fit a linear regression of each annual or calendar-month summary against calendar year. Slopes are expressed per decade. To allow for serial dependence between annual observations, uncertainty uses a lag-3 Newey-West covariance estimate without prewhitening, with finite-sample adjustment and a t reference (Newey and West 1987; Zeileis 2004). These intervals are approximate; daily KBDI observations are not treated as independent replicates. Lags refer to retained annual observations, so missing years introduce irregular spacing.

We report pointwise 95% intervals and Benjamini-Hochberg-adjusted p -values (Benjamini and Hochberg 1995). Adjustment covers 12 monthly tests within each outcome and endpoint, and five annual outcomes within each endpoint. Annual rainfall and mean daily maximum/minimum temperature provide context for the two principal drought summaries. We do not interpret their regressions as a causal decomposition of KBDI change. The 2020 endpoint, corresponding to the original study period, is recomputed with the same updated observations and corrected implementation as an endpoint sensitivity check.

3.3. Robustness and spatial correspondence

We evaluate 27 combinations of annual mean rainfall (55, 60, 65 inches), initial KBDI (0, 400, 800), and complete-day spin-up (180, 365, 730 days). These values define sensitivity scenarios rather than tuned parameters. Additional trend fits use record starts of 1960 and 1980 and annual covariance lags of 0, 1, 3, and 5. We compare original and corrected algorithms using identical refreshed observations and eligible annual periods. High-deficit-day sensitivity also includes thresholds of 152.4, 160, and 177.8 mm, retaining the same annual years as the primary 165.1-mm analysis.

For a descriptive ENSO adjustment, we regress each monthly deficit mean on year and contemporary monthly Southern Oscillation Index (SOI) from NOAA PSL (NOAA Physical Sciences Laboratory, [n.d.](#)). The shorter common record and adjusted monthly test family are reported explicitly. This adjustment neither identifies ENSO's causal effect nor constitutes a forecast using only information available before a season.

For each PRISM cell, we calculate temporal correlations with the station series on aligned eligible dates. We report both raw squared correlations and squared correlations after subtracting each location's mean calendar-day seasonal cycle. The latter separates anomaly correspondence from shared seasonality. Forest-area-weighted averages summarize the cellwise statistics; they are not the squared correlation of an independently observed forest-wide mean.

3.4. Seasonal wildfire prediction as an application

We model the number of natural wildfires during May-July with a negative binomial distribution. For April 30 deficit D_y^{cm} in centimeters,

$$N_y \sim \text{NegBin}(\mu_y, \theta), \quad \log \mu_y = \beta_0 + \beta_1 D_y^{cm},$$

where the variance is $\mu_y + \mu_y^2/\theta$. Maximum-likelihood estimation uses `MASS::glm.nb` (Venables and Ripley 2002). An intercept-only negative binomial model provides the climatological baseline. Year-only and drought-plus-year models are specification checks, rather than winners selected for operational use. The fixed seasonal window requires no varying-duration offset.

Hindcasts train only on earlier eligible seasons, beginning with 15 training seasons. The 30 eligible natural-fire seasons yield 15 evaluation seasons, 2010-2024. Models are compared using identical targets and evaluation years, with mean absolute error (MAE), root mean squared error (RMSE), and mean negative log probability of the observed count. Smaller values are better. This corrects the earlier notebook’s mismatch between natural-fire predictions and all-fire observations and avoids training on later seasons to predict an earlier one.

Uncertainty in the paired MAE difference uses 2,000 circular moving-block bootstrap resamples of evaluation-year errors, with three-year blocks and a fixed seed. This approximate interval resamples the realized hindcast errors; it does not refit the entire model-selection process. Negative binomial count intervals condition on fitted coefficients and dispersion. We do not represent these intervals as Bayesian posterior predictions or as including parameter uncertainty. All evaluations are retrospective: archive revisions and source publication delays have not been reconstructed as they would have been known at a historical issue date.

4. Results: long-term station-derived drought change

4.1. Annual mean deficit and high-deficit exposure increased

The complete eligible annual record supports increasing station-derived drought exposure (Figure 2; Table 1). Mean annual deficit increased by 2.63 mm per decade (95% interval: 0.58-4.67), and days with KBDI above 650 increased by 2.59 days per decade (0.67-4.51). Both annual drought outcomes retain adjusted p-values below 0.05 when considered with the three contextual weather outcomes. The estimates summarize a variable record with substantial differences among individual years; they do not imply a monotonic increase or provide an extrapolation beyond the observed period.

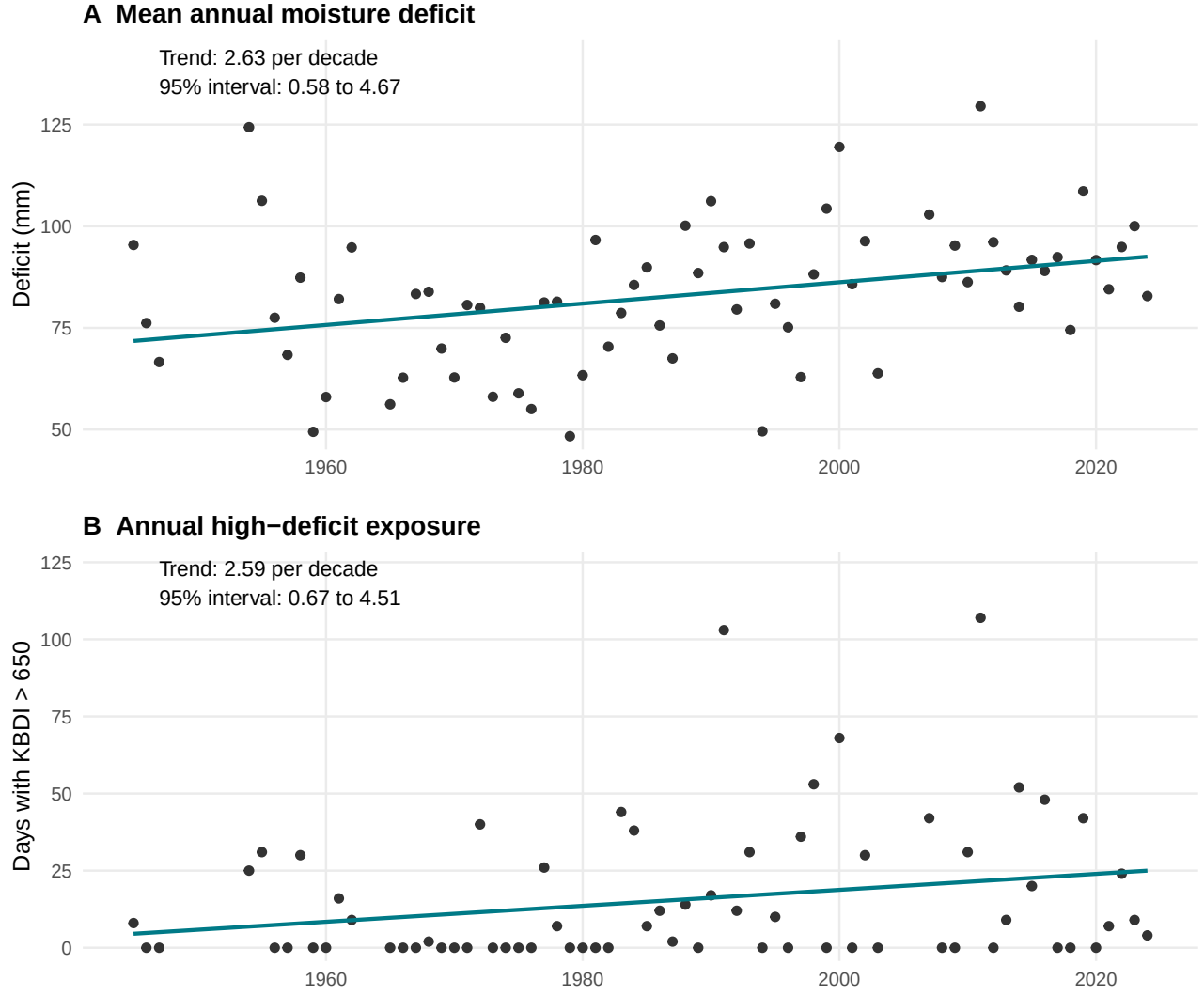


Figure 2. Annual station-derived drought change. (A) Mean annual moisture deficit and (B) days with KBDI above 650, for 69 complete eligible years spanning 1945–2024. Points are annual values and lines are least-squares fits. Slope annotations report changes per decade with pointwise 95% intervals using lag-3 annual covariance. Missing or spin-up-affected years are excluded, not filled.

Annual outcome	Change per decade	95% interval	Adjusted p	Years
Mean deficit (mm)	2.63	0.58 to 4.67	0.021	69
Days with KBDI > 650	2.59	0.67 to 4.51	0.021	69
Rainfall (mm)	-19.06	-53.48 to 15.37	0.274	78
Mean daily maximum temperature (degrees C)	0.200	0.115 to 0.285	<0.001	75
Mean daily minimum temperature (degrees C)	0.141	-0.032 to 0.313	0.135	74

Table 1. Annual trends from the updated complete-period analysis. All effective annual records end in 2024; drought records begin in 1945 and contextual weather records in 1944, with variable-specific gaps. Intervals are pointwise, whereas p-values are adjusted across the five outcomes.

Mean daily maximum temperature also increased, by approximately 0.20 degrees C per decade. The rainfall interval includes both decline and increase, and the minimum-temperature interval includes zero. These results are compatible with more than one explanation for increased deficit. In particular, they do not establish a significant decrease in annual rainfall or quantify the part of the deficit trend caused by warming.

4.2. May has the clearest monthly drying signal

Monthly deficit slopes are positive in point estimate throughout the year, but their magnitudes and uncertainty differ (Figure 3). May's increase is 4.64 mm per decade (95% interval: 1.68-7.61), with an adjusted p-value of 0.031. It is the only calendar month meeting the adjusted 0.05 threshold. Positive slopes in August, September, and October have pointwise intervals above zero, but do not meet that threshold after adjustment across the monthly family.

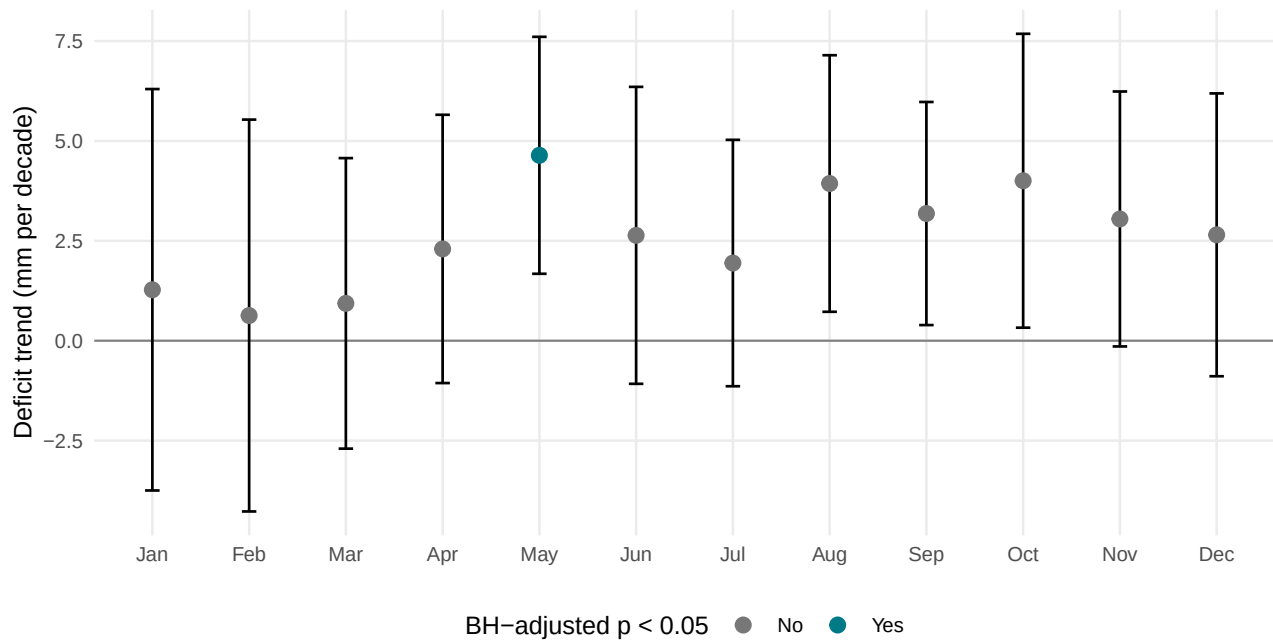


Figure 3. Seasonal structure of drought change. Slopes of monthly mean deficit against year, expressed in mm per decade, with pointwise lag-3 covariance intervals. Color identifies months meeting the Benjamini-Hochberg-adjusted 0.05 threshold across 12 monthly tests. Available complete monthly records span 1945-2025; actual ending years and sample sizes vary by month. The month comparison is exploratory, not a preregistered May-specific test.

April's slope is 2.30 mm per decade, with an interval of -1.06 to 5.65 and an adjusted p-value of 0.265. Thus the updated evidence does not sustain the earlier paper's emphasis on a significant April increase. May remains relevant to the seasonal setting of fire, but a positive May trend is not evidence that all months are drying at an established rate or that the fire season is lengthening.

4.3. Robustness supports the mean-deficit result but qualifies exposure trends

May’s point-estimate slope ranges from 4.19 to 5.24 mm per decade across the 27 KBDI settings. Its unadjusted 95% interval remains above zero in every setting. These are overlapping sensitivity analyses, not independent replications or a joint confidence statement. The corrected and original algorithms give very similar mean annual slopes on identical eligible observations: 2.63 and 2.66 mm per decade, respectively. The annual increase is therefore not produced by the implementation correction alone.

The mean-deficit trend also remains positive in later-start records. For the record beginning in 1960, the slope is 4.35 mm per decade (2.88-5.82); for the record beginning in 1980 it is 3.17 (0.89-5.46), using the primary covariance lag. High-deficit-day trends are more period-sensitive. The post-1980 estimate is 0.63 days per decade with an interval of -4.27 to 5.53. The long-record exposure increase should therefore not be described as an established recent acceleration (Supplementary Figure S2).

Changing the high-deficit threshold changes the result’s magnitude and uncertainty. On the same 69 annual records, the original paper’s 160-mm threshold gives 2.80 additional days per decade (0.56-5.04). At 152.4 mm the point estimate is positive but its interval includes zero; at 177.8 mm the increase is smaller with a positive interval. These exploratory checks support reporting the threshold explicitly rather than claiming an identical result for every definition of high deficit (Supplementary Table S2).

With contemporary SOI adjustment, May’s year slope remains positive at 4.82 mm per decade (1.22-8.41), but its adjusted monthly p-value is 0.104. The common May record contains 69 eligible observations spanning 1952-2025. It would therefore be too strong to claim that ENSO adjustment confirms significant May drying across the tested monthly family. Similarly, describing SOI as the cause of the observed deficit change is not supported by this regression.

4.4. Spatial and soil-moisture comparisons delimit the interpretation

Across the 170 intersecting PRISM cells, the area-weighted mean raw squared correlation with station-derived deficits is 0.77. After removing each location’s mean calendar-day seasonal cycle, the corresponding anomaly statistic is 0.72 (Supplementary Figure S3). Shared seasonality thus explains part, but not all, of the correspondence. These cellwise squared correlations indicate similarity in temporal variations during the short historical comparison; they do not establish unbiased forest-wide moisture estimates.

Because PRISM uses station observations and this comparison is limited to 2009-2018 with spin-up exclusions, it cannot independently validate the long-term station trend. We retain the station-derived description of the main finding rather than treating these correlations as evidence of equivalent change throughout ANF.

The independent Wakulla comparison provides a different check. Across depths, raw correlations between measured moisture and the preceding day’s index range from -0.11 to -0.42; removing month-of-year means gives -0.09 to -0.42. The inverse sign is physically expected, but the correspondence is modest. Record gaps, pronounced level shifts, and sensitivity to depth and date alignment qualify interpretation (Supplementary Figures S4-S5 and Table S9). We report this as exploratory correspondence, not calibration of absolute water deficit or independent verification of the historical trend.

5. Application: pre-season drought and natural wildfire counts

The drought-only negative binomial model has a positive coefficient on April 30 deficit. In the full eligible sample, the coefficient is 0.168 per centimeter (standard error 0.046), equivalent to an estimated 18.3% change in expected seasonal count per additional centimeter, calculated as $100[\exp(\beta_1) - 1]$. This is a fitted association, not a causal effect of changing moisture deficit or evidence that a long-term drought trend must increase future fire counts.

In preceding-year hindcasts, drought-only MAE is 8.06 fires per season compared with 9.93 for the climatological baseline (Figure 4; Table 2). RMSE and negative log score also improve in point estimate. However, the paired MAE improvement is 1.87 fires with an approximate 95% interval of -0.26 to 4.02. With only 15 evaluation seasons, the evidence does not establish a reliably positive improvement for natural-fire forecasts.

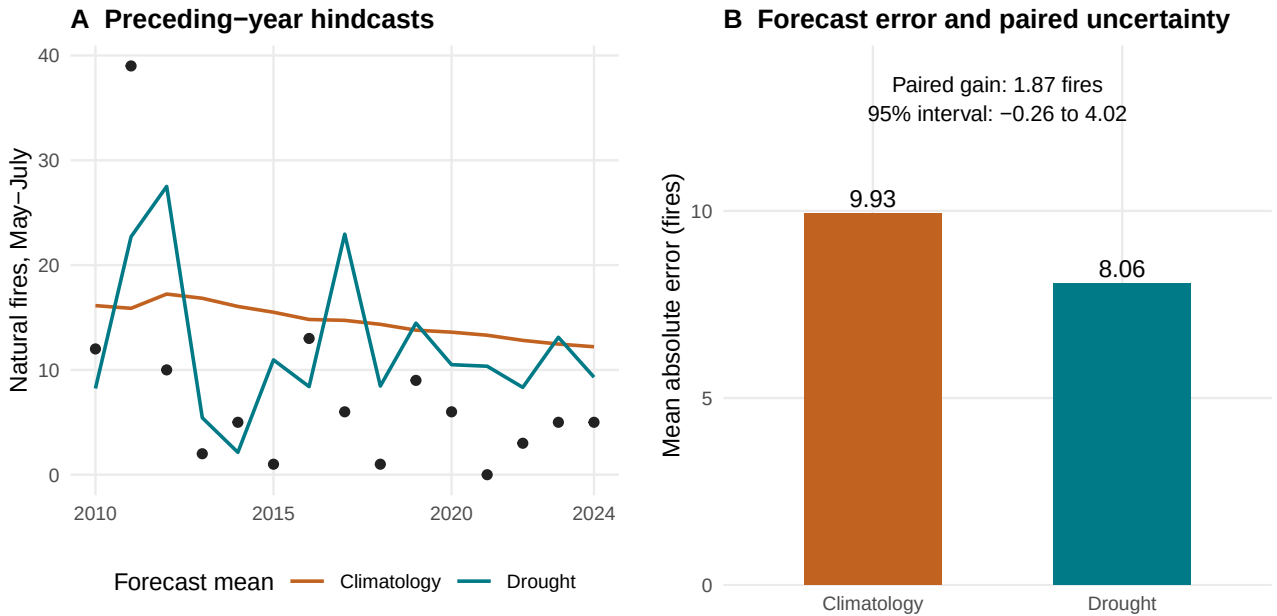


Figure 4. Wildfire prediction as an application. (A) Observed May-July natural-fire counts (black points) and forecast means from drought-only and climatological negative binomial models, evaluated in 2010-2024 using only preceding eligible seasons for training. (B) MAE for the two primary models, with the paired improvement and its approximate three-year-block bootstrap interval. These are retrospective hindcasts, not forecasts issued in real time.

Natural-fire model	MAE (fires)	RMSE (fires)	Mean negative log score
Climatology	9.93	11.18	3.273
April 30 drought	8.06	9.45	3.175
Year trend	9.08	11.36	3.197
Drought and year trend	7.13	9.53	3.103

Table 2. Identical 15-season evaluation sets for the natural-fire response. Year-only and combined models are exploratory specification checks. Ranking several specifications on these same years does

not provide an independent validation of the best-performing specification.

Adding a year trend changes the skill comparison, illustrating that the fire record contains temporal structure beyond the drought predictor. A supplementary antecedent-burn-area check uses an aligned May 1-April 30 window, but final reported sizes might not have been available at a historical forecast date. We do not infer management effectiveness from that predictor’s performance, and we do not use the fitted count model to project future wildfire activity from extrapolated drought trends.

6. Discussion

6.1. What the updated record establishes

The principal result is an increase in station-derived annual moisture deficit, together with increased exposure above a specified high-deficit threshold, over the available long record. The seasonal comparison places May ahead of April as the clearest monthly signal under the present specification and multiplicity adjustment. The long record and seasonal analysis provide the principal evidence; the small natural-fire evaluation sample gives a more tentative assessment of predictive utility.

The agreement between corrected and original algorithms on the same annual periods supports the persistence of the mean-deficit finding. It does not remove uncertainty arising from observations or missing-data choices. Likewise, robustness to the tested KBDI settings supports the May pattern within this index framework, but is not a validation of KBDI against direct soil-water measurements. Differences between long-record and later-start exposure trends show why the estimated period belongs alongside any rate of change.

Long-term change and operational drought severity also require different reference frames. Hoylman, Bocinsky, and Jencso (2022) caution against treating a long historical distribution as stationary when assessing present conditions. Here we retain a fixed KBDI formulation to describe change through time; we do not estimate contemporary return periods from the pooled record. Updating a monitoring baseline would answer a different question and would not remove the need to examine the full record for change.

Annual means and threshold counts describe two aspects of exposure. They do not resolve drought onset, duration, recovery, or rainfall interruptions. The KBDI-based drought-feature framework of Elias, Faour, and Mouillot (2024) illustrates how these characteristics can be separated in a Mediterranean setting. Applying that approach locally could test seasonal timing, but our monthly slopes alone do not establish a lengthening drought or wildfire season.

6.2. Mechanisms, scale, and management interpretation

Temperature, rainfall timing, and antecedent conditions jointly influence the calculated deficit. An increase in maximum temperature is consistent with one contribution to drying, but the regressions here do not separate those contributions or attribute them to anthropogenic forcing. Regional attribution studies use additional modeling and evidence (Abatzoglou and Williams 2016); our single-station analysis does not perform that attribution.

Ignition, suppression, prescribed fire, fuels, and reporting all influence observed fires in this managed landscape. Hashida, Lewis, and Cummins (2025) explicitly model the interaction between climate,

prescribed burning, and large wildfire in the southeastern United States. Southeast FireMap also provides regional evidence on changes in frequent burning across ownerships and landscapes (Nowell et al. 2026). Those burned-area and management analyses concern different outcomes from our ignition counts. Their results support considering management in future local work without implying that our count model measures its effectiveness. A weak or uncertain burn-area predictor cannot show that management is effective, and a positive drought coefficient does not identify how management would change the response. The forecast application instead shows how a drought indicator can be evaluated against an explicit baseline with uncertainty.

6.3. Limitations and next research steps

The station series has not undergone a dedicated homogenization analysis. Changes in siting, instruments, or observation practices could contribute to apparent long-term change. Reviewing station history and comparing neighboring long-term records are therefore priorities. The complete-period policy avoids undocumented imputations but may select an unrepresentative set of years if missingness is related to weather conditions. KBDI resets and the fixed rain climatology are further assumptions, even though sensitivity checks address part of their influence.

Trend intervals use an approximate covariance treatment with irregularly spaced retained annual observations. Alternative time-series or block-based climate inference could refine uncertainty. The May comparison remains exploratory, and the shorter ENSO-adjusted record does not justify a stronger monthly-family claim. The 2009-2018 spatial check cannot supply a homogenized forest-wide long-term trend; a suitable spatial record or independent soil/fuel-moisture measurements would be needed to extend that interpretation. The Wakulla observations begin much later and show level changes whose causes are unresolved. They add independent local context but do not validate the 1944-onward trend. Consistent with Hoylman et al. (2024), depth and season should be specified in any soil-moisture assessment; maintenance history and temporal uncertainty analysis are prerequisites for a stronger validation claim.

For wildfire prediction, only 15 hindcast seasons are available. Source release delays were not reconstructed, conditional count intervals omit parameter uncertainty, and comparisons among added specifications reuse the same test period. Independent future evaluation, a longer stable fire record, and an explicitly reconstructed issue-date workflow would be needed before judging operational utility.

7. Conclusions

The Tallahassee airport record shows increasing KBDI-derived annual moisture deficit and more days above a specified high-deficit threshold across 69 complete eligible annual records spanning 1945-2024. May has the clearest monthly drying signal under adjustment for 12 comparisons, while April's trend remains uncertain. These findings characterize long-term station-derived drought exposure near ANF. Historical airport-grid correspondence and seasonal natural-fire hindcasts provide supporting context and an application, but do not establish a forest-wide causal climate-change effect or a validated operational wildfire forecast.

Acknowledgements

The initial work was conducted by Zach T. Law as a graduate student at Florida State University and formed the basis of the initial manuscript [10.31223/X5H350](#). His contribution to the foundation of this study is gratefully acknowledged. This work was supported by Florida State University.

Data and code availability

Source data are available from NOAA GHCN-Daily and NOAA PSL, PRISM, the Forest Service FPA FOD archive, and USDA NRCS SCAN. The project repository is <https://github.com/jelsner/KBDI>. The revised reproduction workflow uses `scripts/run-all.R`; `scripts/paper-figures.R` redraws all manuscript figures from prepared results, and `scripts/paper-tables.R` exports the tables. The supplemental Wakulla comparison is reproduced with `scripts/soil-moisture-check.R` and `scripts/paper-soil-supplement.R`. Small source snapshots, derived data, settings, and checksums are documented in the repository. Large historical PRISM grids remain local, with a compact forest extraction sufficient to repeat the spatial comparison. Figure and analysis manifests identify the specific inputs used here. The repository URL identifies the project; this revision requires its own release or commit identifier before publication.

Supplementary material

Daily structure of the station record

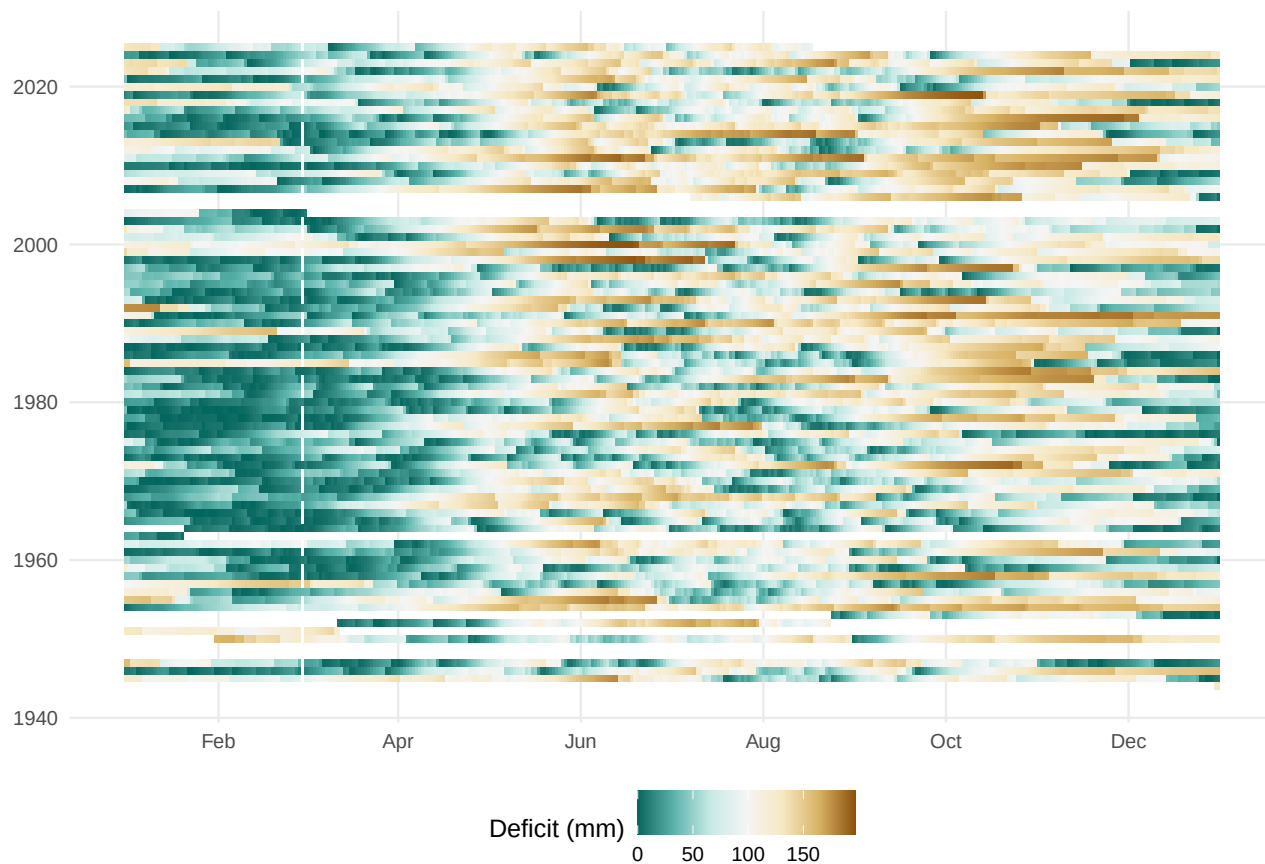


Figure S1. Daily station-derived moisture deficit. KBDI-equivalent deficit on eligible days in complete candidate calendar years through 2025. Missing and spin-up-affected days are blank. Calendar dates are aligned to a leap-year reference so February 29 is represented explicitly; it is not treated as a common non-leap-year day. The display describes daily structure, whereas trend inference uses complete monthly and annual summaries.

Record-period and covariance sensitivity

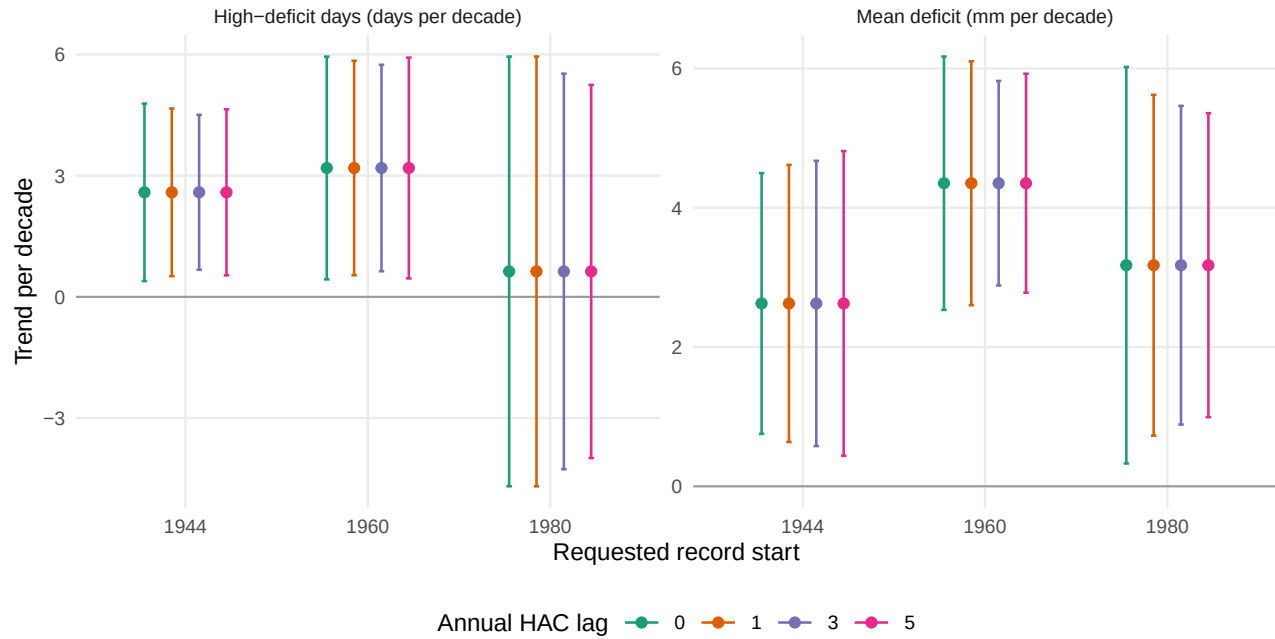


Figure S2. Sensitivity to record start and covariance lag. Point estimates and pointwise 95% intervals for annual mean deficit and high-deficit days, using requested record starts of 1944, 1960, and 1980 and annual covariance lags of 0, 1, 3, and 5. The first eligible annual KBDI record in the full calculation is 1945. High-deficit days use KBDI greater than 650. Actual sample sizes vary with the retained record.

Complete estimates are in Supplementary Table S5. HAC lags apply to retained annual observations, not a regularized calendar-year series. These are sensitivity fits on overlapping records, not independent replications.

Historical PRISM correspondence

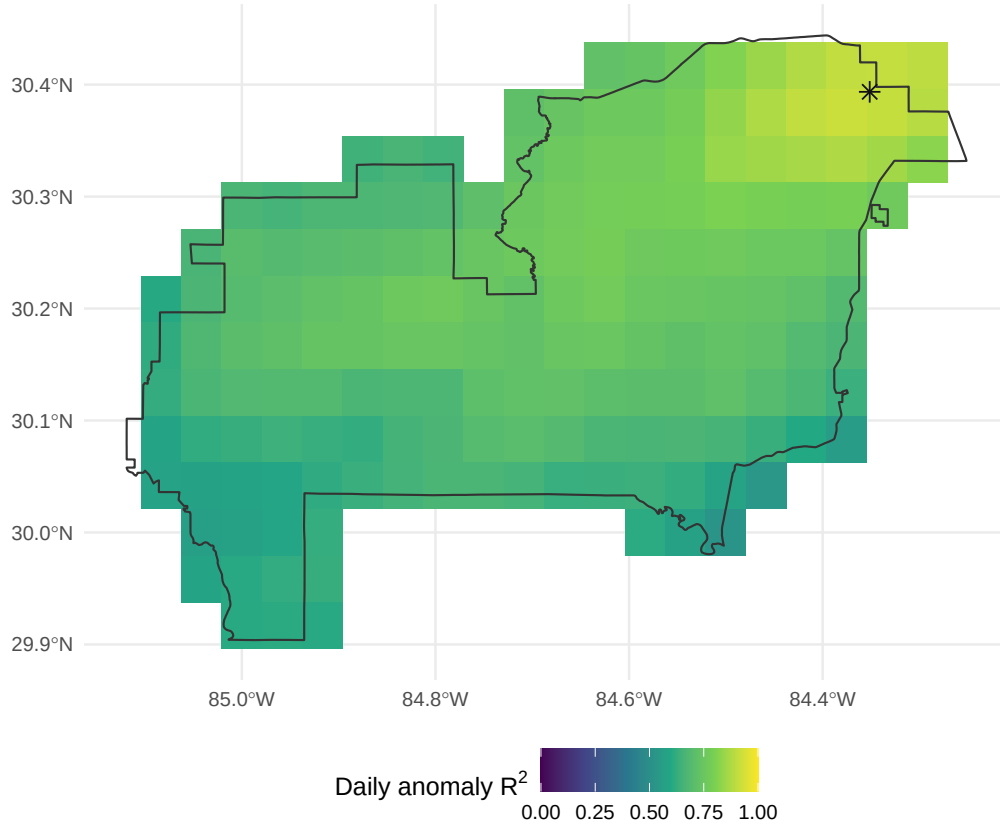


Figure S3. Airport-forest daily anomaly correspondence. Squared correlation between each PRISM cell's KBDI-derived deficit and the station-derived deficit after removal of each location's mean calendar-day seasonal cycle. The polygon outlines the fixed ANF footprint and the star marks the airport station. The original 2009-2018 PRISM archive is used with complete-day spin-up; it has not been extended. Grid cells are shown at their native resolution, including cells only partly intersecting ANF. Area-weighted summaries use each cell's forest overlap.

The area-weighted mean raw squared correlation is 0.77 and the anomaly statistic is 0.72. These are means of cellwise statistics, not the squared correlation of a measured forest-wide mean. PRISM incorporates station observations and this is not independent validation. Cellwise counts, bias, RMSE, area weights, and April 30 correspondence are in Supplementary Table S7.

Exploratory comparison with Wakulla soil moisture

Observations, timing, and quality control

The Wakulla #1 SCAN site lies inside the fixed ANF footprint, 12.03 km from the Tallahassee airport. Its five soil-moisture sensors sample depths of 2, 4, 8, 20, and 40 inches (5.08-101.6 cm). The first four records begin on 10 December 1996 and the deepest begins on 29 April 1997 (USDA Natural Resources Conservation Service, [n.d.](#)). The soil-moisture observations are independent of the airport weather

inputs used to compute KBDI. Following the depth-specific motivation of Hoylman et al. (2024), we report all depths rather than selecting the sensor with the highest correspondence.

NRCS’s DAILY SMS product contains instantaneous midnight observations, not daily averages. We pair midnight moisture on date D with nominal end-of-day KBDI on D-1, and retain same-date pairing as a sensitivity check. The SCAN station uses UTC-5; the airport daily observation window may not coincide exactly with local midnight. No lag is optimized to increase agreement.

Primary comparisons retain only NRCS QC flag V (valid) observations bounded between 0 and 100% and KBDI following at least 365 consecutive complete input days. The API request excludes suspect observations. Both QC and QA flags are preserved in the paired dataset. A sensitivity adds N observations, which lack an automated validation profile; E and other flags are excluded. The source snapshot extends to 12 October 2026, but the last V-flagged soil observation is 23 September 2024. Primary pairing therefore ends with KBDI on 22 September 2024. Missing days are not filled.



Figure S4. Wakulla soil-moisture observations. Monthly means of eligible midnight observations by sensor depth, requiring at least 80% of calendar days to have paired observations. Lines break across missing or insufficiently covered months. Panels have different vertical scales. Pronounced level changes are visible, but their causes have not been established from maintenance history.

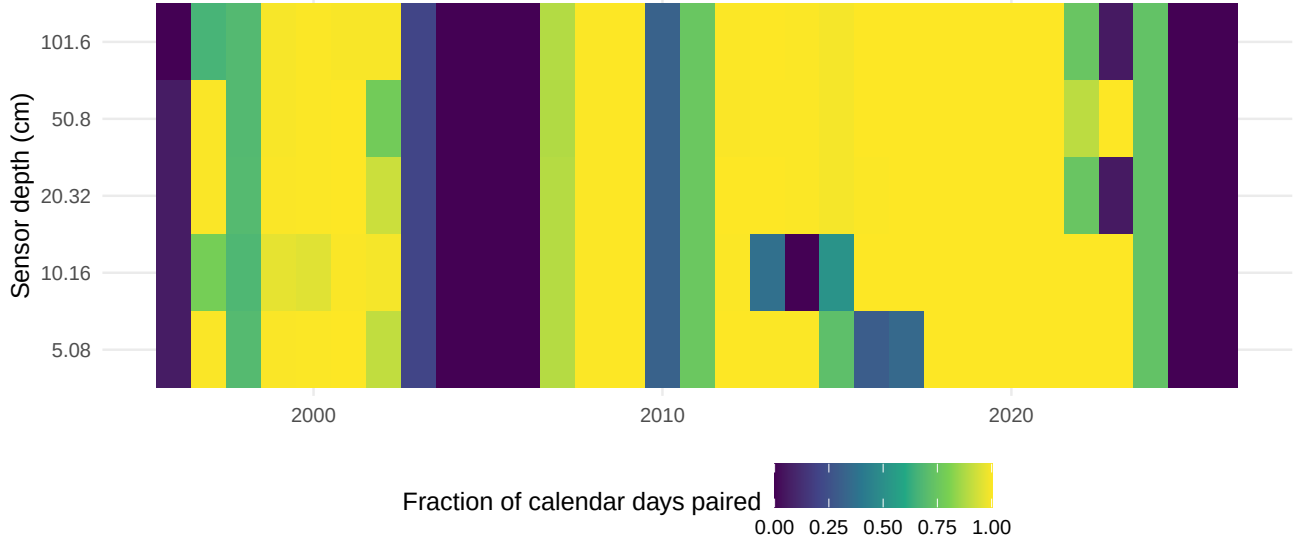


Figure S5. Coverage of the Wakulla comparison. Fraction of calendar days with V-flagged, physically bounded soil moisture and an eligible paired KBDI value. Years with no eligible pairs are shown explicitly. The first and last years are partial source years; the denominator remains the full calendar year.

Descriptive correspondence

We report raw Pearson and Spearman correlations. To remove the broad seasonal cycle, we separately subtract each variable’s mean for its calendar month, calculated on the same paired dates, and correlate the residuals. This month-of-year centering is simpler than the standardized soil-moisture-index methodology in Hoylman et al. (2024) and does not reproduce that study. We also center within each year/month as a diagnostic of shorter-term correspondence despite persistent offsets. Results are reported for all months, May, and May-July, using both the full available record and 2007-2024. The later period starts after the prominent multi-year gap; it is a sensitivity choice, not evidence that subsequent observations are homogeneous.

Depth (cm)	Paired days	Raw Pearson r	Month-anomaly r
5.08	7,617	-0.230	-0.175
10.16	7,367	-0.114	-0.092
20.32	7,783	-0.348	-0.308
50.80	8,124	-0.381	-0.349
101.60	7,655	-0.416	-0.423

Table S9. Primary full-record, all-month descriptive correspondence, using midnight soil moisture and preceding-day KBDI. Correlations are negative when higher drought deficit corresponds to lower soil moisture. Paired-day counts are not independent sample sizes. The full diagnostic table contains the seasonal, period, quality-flag, and timing sensitivities. Table S10 reports annual coverage.

Month-anomaly correlations for 2007-2024 range from -0.20 to -0.34. Using same-date KBDI in the full record gives raw correlations from -0.14 to -0.41. Thus the expected sign persists, while strength depends

on depth, period, and timing. Daily values are serially dependent; we report no ordinary correlation p-values or inferential intervals. The analysis is exploratory and does not involve tuning KBDI to the observations or evaluating a fitted soil-moisture model out of sample.

Interpretation and limitations

NRCS documents a loam conversion equation for these sensors (USDA Natural Resources Conservation Service, [n.d.](#)). V flags do not establish stable calibration or rule out sensor drift. The series show pronounced level changes, including at approximately 10 cm around 2001, 5 cm around 2017, and 51 cm during 2020-2022. These are review targets, not diagnosed instrument failures. We do not delete intervals solely because doing so would improve correlation, and do not fit trends to these records. Maintenance and calibration histories are needed before defining defensible segments or adjustments.

KBDI-equivalent deficit in millimeters and volumetric soil moisture in percent are different quantities. An absolute deficit bias or RMSE would require a specified soil profile, storage capacity, and separately justified calibration. The observed inverse correspondence supports a limited interpretation of KBDI as a local dryness indicator. Its modest strength also cautions against substituting KBDI for measured soil moisture. This single-profile comparison cannot verify the 1944-onward drought trend or represent the entire ANF. Any stronger validation would require sensor-history review, a prespecified seasonal normalization, temporal uncertainty estimates, and evaluation on data not used for calibration.

High-deficit threshold sensitivity

Deficit threshold (mm)	Equivalent KBDI	Days per decade	Pointwise 95% interval
152.4	600.0	3.04	-0.29 to 6.36
160.0 (original paper)	629.9	2.80	0.56 to 5.04
165.1 (primary revision)	650.0	2.59	0.67 to 4.51
177.8	700.0	1.32	0.37 to 2.27

Table S2. All threshold checks retain the same 69 complete eligible annual periods, with lag-3 covariance. These exploratory pointwise intervals are not adjusted as a new family of confirmatory tests. The thresholds do not define validated local ecological damage levels. The machine-readable table retains full precision.

Additional tabular diagnostics

- Table S3: KBDI settings: 27 combinations of rainfall climatology, initial deficit, and spin-up, for April-July slopes. Original units in this table are mm per year; multiply slopes and intervals by 10 to express change per decade. Intervals are unadjusted.
- Table S4: ENSO adjustment: year and contemporary SOI coefficients for each month. Year slopes are mm per year; SOI coefficients are mm per SOI unit. Adjusted p-values are calculated across months within each term.

- Table S6: original versus corrected algorithm: identical observations and complete eligible years; slopes are mm per year.
- Table S8: weather gaps: missing or rejected required daily inputs. The audit spans the full daily processing period, including dates outside complete climate-trend years.

The full monthly deficit estimates are in Supplementary Table S1, with slopes in mm per decade. The main manuscript tables are Table 1: annual trends and Table 2: natural-fire forecast metrics.

Reproduction

Run `Rscript scripts/run-all.R` from the project root to rebuild the analysis, publication figures, tables, and HTML previews. Figure-only regeneration uses `Rscript scripts/paper-figures.R`; it requires existing prepared results and makes no network requests. The Wakulla diagnostic uses `Rscript scripts/soil-moisture-check.R`, followed by `Rscript scripts/paper-soil-supplement.R` to export its figures and tables. The complete workflow includes these cached-data steps. Every figure is exported as a vector PDF and a 300-dpi PNG; figure manifests record inputs and export checksums.

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